Shape invariant modelling of trial based fMRI data

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Introduction

Most previous component analyses of fMRI data have avoided working directly with the tri-linear structure, but resorted to bi-linear models such as ICA, PCA, and NMF. Multi-linear decomposition can exploit consistency over trials and contrary to bi-linear decomposition render unique representations without additional constraints. However, they can degenerate if data does not comply with the given multi-linear structure, e.g., due to shape variations.

Materials and Methods

The tri-linear CANDECOMP/PARAFAC (CP) of space-time-trial neuro-imaging data decompose the data into spatial and temporal signatures while accommodating trial-to-trial amplitude variability [1]. The model is however unable to accommodate trial variability such as the inevitable inter-trial delay and shape variations of typical neuroimaging experiments. Delay modelling has recently been treated using the ShiftCP model in [3], however, multiple delays which can occur for instance due to the cardiac or respiratory cycles or shape differences in activity between trials cannot be modelled within the ShiftCP representation. To accommodate such trial variability we propose the convolutive CP model (ConvCP), as illustrated in figure 1.

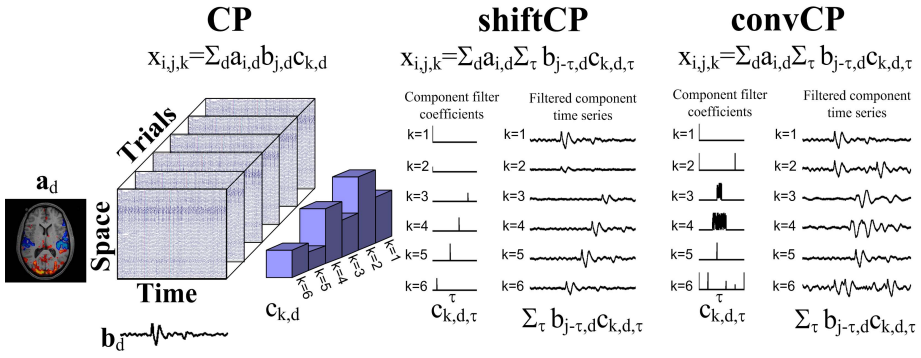

Figure 1: Illustration of the CP model to the left as well as the extension to the shiftCP and convCP model. The CP model decompose the space×time×trials data array into the component profiles $\boldsymbol{a_d}$, $\boldsymbol{b_d}$,$\boldsymbol{c_d}$ pertaining to the space, time and trials modality respectively. The shiftCP model further allows for a specific delay for each component in each trial. As such the shiftCP model can be considered a restricted convCP such that each trial has one non-zero coefficient τ in the convolutive component filter $\boldsymbol{C_{:d:}}$ where *:* index over all trials *k* and delays τ respectively. Thus, contrary to the shiftCP model, the convCP model can account for multiple delays within the complete convolutive filter $\boldsymbol{C_{:d:}}$ as well as variability in shape as demonstrated by the filtered component time series given to the right of the convolutive filters.

The ConvCP model was updated alternating between (***a***, ***b***, ***c***) according to the following negative log-posterior (disregarding constants and with ***a*** and ***b*** normalised componentwise),

$$\frac{1}{2}\sum_{i,j,k}\|x_{i,j,k}-\sum_{d,\tau}a_{i,d}b_{j-\tau,d}c_{k,d,\tau}\|_F^2+\lambda\sum_{k,d,\tau}|c_{k,d,\tau}|$$

where λ is a prior parameter used to control the sparsity of the convolutive filter.

The BOLD fMRI data consisted of a single slice acquired at 3Hz in a para-axial orientation parallel to the calcarine sulcus using an EPI sequence (field strength 1.5T). Each trial consisted of 10 seconds (30 scans) of fixation, 10 seconds stimulation and 20 seconds of post-stimulus fixation. The visual stimulus was delivered as an annular full-field checkerboard reversing at 8 Hz. The data set consisted of 10 trials and was pre-processed as described in [2]. To cover the stimulation period we set the convolutive filter length T=40 samples. To capture a strictly event related component in the data we constrained the last of the convCP components to be instantaneous. Then, the remaining convolutive components should model consistent confounding effects not phase locked to the event. For comparison we included a regular CP analysis as well as the shiftCP model [3]. The convergence criterion for the algorithm was set as termination when the relative change of the log-posterior was less than 10^{-6} or when the algorithm had run for 1000 iterations. Since the optimization problem is non-convex the decompositions with highest log-posterior of 5 runs were chosen.

Results

As shown in figure 2 all three methods were able to extract the visual activity, however, in the convCP model the instantaneous component is more localised in the visual regions and is isolated in one component contrary to the CP and shiftCP model. Contrary to the CP and shiftCP decompositions no crosstalk between components is found in the convCP. When pruning the filter coefficients (λ=100) the convCP model does not reduce to the shiftCP model. Instead the components model cardiac cycle effects prominent at frequencies around 0.8-1.2 Hz as well as low frequency drift.

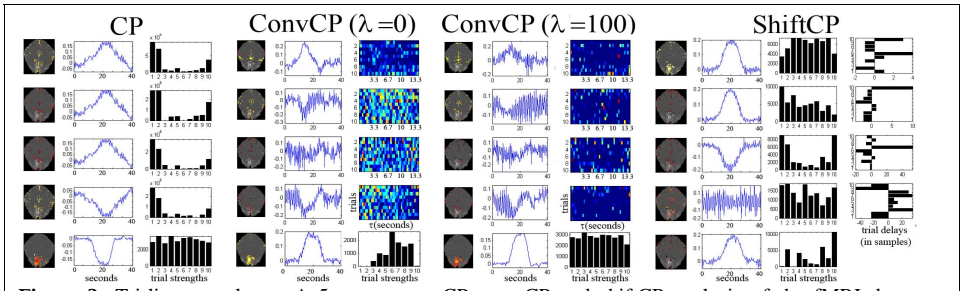

Figure 2: Tri-linear analyses: A 5 component CP, convCP and shiftCP analysis of the fMRI data set. Spatial profiles are thresholded to present the 5% of pixels with highest activity. Given are also component time series as well as trial strengths, convolutive filters and delays for the various models respectively.

Discussion and Conclusion

The convCP model more adequately model the data than the CP and shiftCP models as the latter form so-called cp-degenerate solutions dominated by between component cancellations due to modelling inadequacy. Thus, delay modelling within a convolutive representation is important for multi-linear decompositions of trial based neuroimaging data enabling contrary to shiftCP and CP modelling of multiple trial delays as well as shape variation. Contrary to CP and shiftCP the convCP is able to both model the visual activity well while at the same time find components related to the cardiac cycle.

Not only are fMRI signals obtained under poor SNRs, the underlying responses to repeated stimuli are only partly reproducible, see e.g., [4]. In this work we have proposed a convolutive method convCP that exploit the tri-linear structure of the data and thereby identify consistent activities across the trials with the flexibility for Both multiple delays and shape variation. The convCP model generalises directly to data of more modalities than three that naturally arise for instance when including modes such as subjects, conditions or runs [1] and also to convolutions across additional modes. Thus, the model forms an efficient framework for modelling of the inevitable shape and delay variability in fMRI experiments.

Bibliography

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